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The Noise-Resilient Brain: Resting-State Oscillatory Activity Predicts Words-In-Noise Recognition

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Abstract

The role of neuronal oscillations in the processing of speech has recently come to prominence. Since resting-state (RS) brain activity has been shown to predict both task-related brain activation and behavioural performance, we set out to establish whether inter-individual differences in spectrally-resolved RS-MEG power are associated with variations in words-in-noise recognition in a sample of 88 participants made available by the Human Connectome Project. Positive associations with resilience to noise were observed with power in the range 21 and 29Hz in a number of areas along the left temporal gyrus and temporo-parietal association areas peaking in left posterior superior temporal gyrus (pSTG). Significant associations were also found in the right posterior superior temporal gyrus in the frequency range 30 to 40Hz. We propose that individual differences in words-in-noise performance are related to baseline excitability levels of the neural substrates of phonological processing.

Keywords

Resting-state; MEG; speech perception; words-in-noise; oscillations; power; rapid auditory processing;
phoneme; STG; HCP

Highlights

- Power of resting MEG activity predicts Words-In-Noise recognition performance
- Significant associations in higher beta and lower gamma frequency band
- Strongest in left-lateralised perisylvian cluster peaking in posterior STG
- Effects are spectrally and spatially consistent with phoneme-level processing

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1. Introduction

Over the last decade, the scope of neuroscientific inquiry has considerably broadened, as the traditional approach to studying the brain through its task-elicited activation, is increasingly assisted and complemented by the interrogation of its task-independent properties (Biswal et al., 2009). Among the factors contributing to the rise in interest in spontaneous brain activity has been the realisation that resting-state (RS) brain activity has the potential to index a number of intrinsic features of the brain. Further, measures of RS brain activity have been shown to be predictive not only of task-related brain activation (Cole, Ito, Bassett, & Schultz, 2016; Mennes et al., 2010, 2011; Tavor et al., 2016), but also of behavioural outcomes (Finn et al., 2016; Fox, Snyder, Vincent, & Raichle, 2007; Fox, Snyder, Zacks, & Raichle, 2006; Mennes et al., 2011). Contrary to traditional hypothesis-driven task-based approaches that aim at characterising how – where and when – the brain processes the given stimulus property, as indexed by brain activation, hypothesis- and task-free approaches aim to characterise inherent features of the brain that shape how information from the outside world is processed. To this extent, the brain's RS activity may be conceived of as a structuring context in which evoked activity occurs.

In this study we used magnetoencephalography (MEG) to characterise the brain's RS activity in terms of spectrally-resolved power. MEG records magnetic field perturbations produced by neuronal electrical activity at high temporal resolution, enabling the decomposition of the broadband signal into spectrally-resolved components. It has been shown that different frequency ranges are functionally distinct (Buzsáki & Draguhn, 2004). Spectrally-specific modulations in amplitude/power of the electromagnetic field associated with neuronal activity are thought to reflect the degree of synchronisation among neuronal populations. Here, we tested whether individual differences in spectrally-resolved MEG power relate to inter-individual variability in a speech perception task in a sample of 88 participants made available as part of the Human Connectome Project (HCP; Van Essen et al., 2013). Specifically, we tested whether spectrally-resolved RS MEG power is predictive of the ability to perceive speech in noise, as

measured by a Words-In-Noise (WIN) test. WIN assesses individuals' ability to recognise isolated monosyllabic words embedded in background noise. The ability to comprehend speech in noise, and acoustically-degraded speech more generally, is known to be highly variable across individuals (Mattys, Davis, Bradlow, & Scott, 2012), and several hypotheses have been advanced regarding cognitive determinants of speech in noise and degraded speech comprehension (Rönnberg et al., 2013; Zekveld, Rudner, Johnsrude, & Rönnberg, 2013). Here, however, we aimed to examine the relationship between RS activity and WIN performance, while controlling for a battery of other, general cognitive and demographic factors. In this way, we hope to make progress in elucidating the neural bases of speech-in-noise comprehension that are determined by intrinsic brain properties, dissociated from cognitive factors.

It is thought that a first step in the analysis of sensory signals is their sampling and quantisation. Cortical oscillations, which are rhythmic fluctuations in neuronal synchrony at specific time scales, have been proposed as a key mechanism responsible for the processing of the incoming continuous speech stream. According to the influential asymmetric sampling in time hypothesis (AST; Giraud et al., 2007; Giraud & Poeppel, 2012; Poeppel, 2003), a "*principled relation*" (i.e., a quasi-isomorphism) exists between the time scales at which meaningful acoustic events in speech occur and those at which the speech perception system operates, by means of cortical oscillations. This hypothesis holds that speech processing is temporally-asymmetric in non-primary auditory areas, with left-hemisphere (LH) mechanisms (i.e., low- γ oscillations in the ~20-50Hz frequency range) preferentially extracting information over shorter (20-50ms) temporal windows and right-hemisphere (RH) mechanisms (i.e., θ oscillations in the ~3-7Hz frequency range) over longer (~150-300ms) windows (Poeppel, 2001, 2003). The slower time scale corresponds to the duration of slow spectrotemporal fluctuations associated with the alternation of syllables and the latter corresponds to a processing or sampling rate suitable for capturing the rapid acoustic features relevant for phonemic identification, such as formant transition

and voice onset time (Delattre, Liberman, & Cooper, 1955; Kewley-Port, 1982; Liberman, Cooper, Shankweiler, & Studdert-Kennedy, 1967; Lisker & Abramson, 1964; Rosen, 1992).

The AST suggests that the evident functional asymmetry of non-primary auditory cortices is related to differences in the distribution of the centre frequency at which neuronal ensembles spontaneously synchronise. These are relatively more skewed towards synchronising at a θ rate in the RH and skewed towards synchronising at a low- γ pace in the LH. There is indeed some evidence for spectral peaks in θ and low- γ frequency ranges in resting electrophysiological activity within primary auditory areas, as observed, for instance, by Lakatos and collaborators (2005) by means of intracranial recordings in macaques. These spontaneous, ongoing oscillations were also shown to predict the activity evoked by noise bursts. Further, consistent with the slight asymmetry in spontaneous activity implied by the AST, it has been shown by means of simultaneous EEG and fMRI recordings in humans that spontaneous activity in the low- γ range at rest correlates best with LH auditory cortical synaptic activity (as indexed by the BOLD signal), whilst RS EEG power within the θ range correlates best with synaptic activity in the RH (Giraud et al., 2007). Finally, Lehongre and collaborators (2011) have shown asymmetries in peak oscillatory responses to rhythmic auditory stimulation in planum temporale and posterior superior temporal sulcus: whilst stronger responses were elicited in the RH by periodicities above 55Hz, the strongest responses in the LH were elicited by periodic auditory stimulation in the 25-35Hz range.

We propose that individual differences in WIN performance may be related to baseline excitability of the speech perception system. While there is evidence for a number of oscillatory regimes to be involved in the processing of language – with θ and low- γ being of paramount interest – evidence that the amplitude of spectrally-resolved spontaneous activity is able to predict a rather high-level speech perception task as WIN recognition has not been reported thus far. To date, the wide majority of studies on task-free brain activity have focused on examining its functional connectivity – i.e., the temporal correlation between spatially remote brain areas which is thought to represent communication – by

means of functional magnetic resonance imaging (fMRI). By measuring coherent spontaneous low-frequency (i.e., <0.1Hz) fluctuations of the blood oxygenation level dependent signal, studies making use of fMRI have demonstrated the existence of a number of large-scale neural networks, which highly resemble the activation and deactivation maps associated with performing perceptual, motor or cognitive tasks (see Van Den Heuvel & Pol, 2011 for a review). Here, in contrast, we use a relatively simple representation of the brain's RS characteristics in a bid to predict a specific behavioural ability. Importantly, rather than measuring information flow over large and distributed networks, as would be the case in connectivity analyses, we aimed at indexing local brain activity and how it relates to individual behavioural differences.

2. Material and methods

2.1. Participants and procedures. Resting-state MEG data from 88 participants were analysed. Mean age was 28 years and 7 months (SD = 4 years, range = 22-35 years). Forty-one participants were female. All of the subjects had normal hearing. The full HCP protocol of participants undergoing MEG is typically completed in a three-day visit (see the Reference Manual for the 1200 Subjects Data Release by the WU-Minn Consortium Human Connectome Project, 2017 for details: <https://www.humanconnectome.org/study/hcp-young-adult/document/1200-subjects-data-release>). RS MEG data acquisitions always preceded WIN test by at least one full day.

2.2. Speech material. The Words-In-Noise test (WIN; Wilson, 2003; Wilson et al., 2007) was used to test participants' ability to recognise single words presented amid varying levels of background noise. The WIN establishes individual signal-to-noise ratio (SNR) thresholds for correct word recognition and, by so doing, measures how much difficulty a person might have listening to speech in a noisy environment. Specifically, participants are presented with isolated monosyllabic words embedded in varying levels of

multitalker babble. They are asked to listen to and then repeat the words. The task becomes increasingly difficult as the background noise gets louder, thus reducing the SNR. Multitalker babble involves several (i.e., six; three male and three female) speakers talking simultaneously about various topics with all of the conversations being unintelligible (Sperry, Wiley, & Chial, 1997). Multitalker babble is the most common environmental noise encountered by listeners in everyday life and is, therefore, highly ecologically valid (Plomp, 1978). Furthermore, it is more sensitive to mild hearing loss as compared to speech-spectrum noise (Findlay, 1976).

Thirty-five words are presented in blocks of five items whilst SNR decreases monotonically through seven levels (26, 22, 18, 14, 10, 6, 2 and -2 dB SNR). The test ends when all the seven lists of items have been completed or when all the five items of a given SNR are not correctly recognised. The examiner assigns one point for each item correctly recognised and no points to incorrect responses. The best raw score a participant can obtain is 35 (all correct) and the worst is zero (none correct). Raw scores are converted back to dB SNR thresholds via the formula: $SNR\ threshold\ (dB) = 26\ dB - .8 * raw\ score$. SNR thresholds can therefore take values from 26 dB (none correct) to -2 dB (all correct). In the sample we analysed SNR thresholds ranged from 7.6 to 2 dB (mean=4.7, SD=1.3). Of note, participants composing the current sample have been tested through either one of two versions of the NIH Toolbox WIN test (V1 and V2). Participants tested through V1 had stimuli delivered via speakers, whilst the majority of V2 participants had stimuli delivered monaurally through headphones, and the better score (lowest SNR) out of the two ears was used as participant score. V1 and V2 scores were normed to be directly comparable across the whole 1200-subjects release. We verified this is the case in our limited subset of 88 participants by testing for mean differences across WIN score in the two groups using the independent 2-group Mann-Whitney U Test (two-way). The test revealed that participants tested through WIN V1 (median = 5.2 dB SNR) did not perform differently from participants tested with VS2

(median = 4.4 dB SNR), $W=846$, $p=.939$. Note, however, that some of the participants labelled as 'V2' could have actually been tested with WIN V1.

2.2.1. Deconfounding procedure. We aimed to establish whether resting MEG power is specifically associated with the ability to recognise words in noise. However, several unspecific factors and variables including demographics (e.g., age) and general cognitive abilities (e.g., working memory, processing speed), may contribute to (i.e., confound) each participants' SNR threshold (Frisina & Frisina, 1997; Humes et al., 1994). For this reason, we exploited the wide range of participant measures and information collected as part of the HCP to control for potential contributions of these factors. A detailed description of the measures collected as part of the assessment is available in Van Essen and collaborators (2013). In short, these measures include demographic information, neurological/psychiatric diagnoses, description of subjects' habits (e.g., sleep, drug consumption, etc.), and a wide range of perceptual, cognitive and emotional tests and questionnaires. Out of the full set of subject measures (reported in the "open access" and "restricted" subject information spreadsheets available here: <http://humanconnectome.org/data>), we selected a subset of 211 variables. The full list of these variables can be found in the Appendix. We then performed a second selection of those measures meeting the criteria outlined in Table 1 (adapted from Smith et al., 2015). This procedure resulted in the selection of a final set of 178 confounds.

<Insert Table 1 about here>

Of these measures, 20 were found to be significantly correlated with WIN SNR after FDR correction for multiple comparisons (Fig. 1). Specifically, seven measures of tobacco consumption and dependence were negatively associated with resilience to noise (positively associated with WIN SNR; $r=.243 - .352$, $p_{(FDR)}=.047 - .013$). This is in line with a large population-based study reporting that, compared to non-

smokers, smokers are more likely to experience difficulties in speech-in-noise understanding in a dose-dependent fashion (Dawes et al., 2014). In addition, also three indices of social withdrawal and perceived social rejection negatively predicted resilience to noise ($r=.244 - .262$, $p_{(FDR)}=.048 - .042$), in line with the reported association between hearing difficulties and social isolation (Ciorba, Bianchini, Pelucchi, & Pastore, 2012; Weinstein & Ventry, 1982). Further, ten measures positively predicted resilience to noise (negatively correlated with WIN SNR), namely both age-adjusted and -unadjusted scores on NIH flanker task ($r=-.354$, $p_{(FDR)}=.027$, and $r=-.348$, $p_{(FDR)}=.016$, respectively), both age-adjusted and -unadjusted scores on NIH card sorting test ($r=-.330$, $p_{(FDR)}=.013$, and $r=-.317$, $p_{(FDR)}=.016$, respectively), both age-unadjusted and -adjusted scores on NIH list sorting test ($r=-.306$, $p_{(FDR)}=.017$, and $r=-.303$, $p_{(FDR)}=.017$, respectively), both age-adjusted and unadjusted score on NIH dexterity test ($r=-.255$, $p_{(FDR)}=.047$, and $r=-.242$, $p_{(FDR)}=.048$, respectively), education level ($r=-.279$, $p_{(FDR)}=.009$), and in-fMRI-scanner accuracy on the language ('Story') task ($r=-.234$, $p_{(FDR)}=.026$). It is interesting to note that (verbal) working memory and executive functions have been highlighted as cognitive contributors to degraded speech comprehension (Rönnberg et al., 2013) and that response inhibition seems to be particularly required to perceive speech-in-noise when noise is verbal as compared to non-verbal (Rouleau & Belleville, 1996), as is the case in the context of the WIN test (multitalker babble). With respect to education, we speculate that it may help compensating for a lower perceptual quality of the auditory object in individuals with sub-optimal (although still normal) hearing-in-noise. Finally, with regards to the in-scanner performance on the language task, it is clear that higher resilience to scanner noise may allow for a clearer perception and thus comprehension of the story to be heard. We nonetheless regressed out every available variable, including those that were not significantly individually associated with the measure of interest because the subject measures taken together are sources of individual differences that we wished to remove, as we aimed at establishing relationships that are specific to WIN (See Fig. S1-S2 for an overview on how scores changed as a result of the deconfounding procedure). In

order to avoid overfitting in the regression, principal component analysis (PCA) was used to reduce the dimensionality of the set of confounds. Before entering the PCA, variables were gaussianised by means of rank-based inverse normal transformation and standardised (to mean=0 and SD=1), by subtracting the sample mean from each individual score and dividing the demeaned score by the standard deviation. The statistical rationale for normalising confounds prior to PCA is to stabilize the variance (reduce heteroscedasticity) and to facilitate its quantification and comparison across the range of measures. Twenty-five principal components, accounting for 80% of the total variance of the set of 132 measures, were regressed out from the original WIN score following the steps described by Smith and collaborators (2015).

<Insert Figure 1 about here>

2.3. RS-MEG data. RS-MEG data was acquired in three runs of approximately six minutes per subject during which participants are asked to remain supine with eyes open. Details on acquisition protocols and hardware specifications can be found in the 1200 Subject Data Release Manual linked above. Briefly, subjects were scanned on a whole head MAGNES 3600 (4D Neuroimaging, San Diego, CA) system housed in a quiet, darkened and magnetically shielded room. The MEG system includes 248 magnetometer channels together with 23 reference channels. Data sampled at 508.63 Hz were downloaded from <https://db.humanconnectome.org/>. We applied a fifth-order Butterworth low-pass filter at 48Hz (by means of FieldTrip's 'ft_preproc_lowpassfilter' implementation) and down-sampled the data to 200 Hz by means of Matlab's 'resample' routine with default input parameters. Raw MEG data underwent the standard HCP MEG data pre-processing pipeline based on independent component analysis (ICA) aimed at identifying and removing artefacts, bad channels and bad segments (2s each). Additionally, single shell volume conduction models (one per participant) were defined in the MEG-system based head coordinate system from segmentation of anatomical MRI T1 images. We computed

the inverse solution using Linearly Constrained Minimum Variance (LCMV) Beamformer filters. These allow source models to be defined on a regular 3D grid in normalized MNI-space with a resolution of 8mm, aligning the subjects in source space. Welch's method was used to obtain the power spectral density (PSD) of each of the source-reconstructed and standardised (over time to mean=0 and SD=1) time series session data (three per participant, mean duration = 281s). The two-sided PSD was computed on eight equally-long time series windows of approximately 62.5s each with 50% overlap from 1 to 40 Hz (in 1-Hz bins) at each source point (3559 voxels of size 8*8*8mm each). PSDs of the three sessions were then averaged within participants for each voxel.

2.3.1. Definition of frequency bands. In order to accommodate the inherent similarity of the power distribution in neighbouring frequencies, *k*-means clustering (1000 replicates, using correlation distances) was used to cluster the 40 frequency bins into 6 wider bins based on the similarity of the spatial distribution of voxelwise power. Evaluation of the optimal clustering solution was based on a two-step procedure. First, whole-brain voxelwise power cross-correlation matrix was inspected visually in order to determine a range of *ks* to test. Once the range of clusters to evaluate was established (4 to 6), the optimal solution was determined using two measures of internal clustering validation measures, namely Dunn's Index (DI; Dunn, 1973), and Silhouette Index (SI; Rousseeuw, 1987). Both indices indicated that *k*=6 represented the best clustering solution. The final frequency bins – mainly corresponding to conventional frequency bands – were as follows: 1-4Hz (' δ '), 5-7Hz (' θ '), 8-15 (' α '), 16-20 ('low- β '), 21-29Hz ('high- β '), and 30-40Hz ('low- γ ').

2.4. Statistical Analyses. Within-subject means of voxelwise power in each frequency band were correlated with the standardised deconfounded WIN score. We evaluated the statistical significance of the clusters by means of permutation testing. Because the sample analysed here is composed by subgroups of monozygotic and dizygotic siblings in addition to non-related participants, we took into account the possible effect of family structure on the null distribution of correlations generated by

permutation by randomly shuffling WIN scores (10000 times) across participant labels in a manner constrained by family structure. Multi-level block permutation (Winkler, Webster, Vidaurre, Nichols, & Smith, 2015) was performed using FSL's PALM utility (<https://fsl.fmrib.ox.ac.uk/fsl/fslwiki/PALM>), and the exchangeability block structure specified in the HCP documentation (<https://fsl.fmrib.ox.ac.uk/fsl/fslwiki/PALM/ExchangeabilityBlocks>). For each frequency band ($n=6$) and voxel ($n=3559$), a t -value was calculated for both the actual and the data-driven null distribution; t -values were then compared to produce p -values (separately for the positive and negative contrasts). Below we report results that are significant at a voxelwise level of $p<.05$, corrected for family-wise error rate (FWER) of the multiple comparisons over the 3559 solution points.

3. Results

RS activity was found to be predictive of WIN performance in two adjacent frequency ranges (Table 2, Figure 2). In both the high- β (21-29Hz) and low- γ (30-40Hz) bands, we observed significant negative correlations between power and WIN SNR, indicative of a positive association between amplitude of the oscillatory activity and the ability to be resilient to noise-induced breakdown of intelligibility. In the high- β frequency band, significant associations clustered around four peaks. The largest and most significant peaks are found in the posterior section of the superior and middle temporal gyri (STG and MTG, respectively) and in a more anterior section of the MTG. We further observed small clusters of correlation in associative areas within the lateral aspect of the middle occipital gyrus and inferior parietal lobule (two and one voxels, respectively). In the low- γ band, we notice a cluster of correlation in the RH in the posterior part of the STG.

<Insert Figure 2 about here>

<Insert Table 2 about here>

272

273 **4. Discussion**

274 This analysis has revealed that topographically- and spectrally-resolved RS MEG power – an index of
 275 spontaneous neuronal synchronisation at various time scales – can predict behavioural performance.
 276 This analytical approach offers an alternative and complementary perspective on mechanisms of brain
 277 functioning as compared to activation studies. Indeed, whilst in the latter type of studies, individual
 278 differences in brain responses to stimulation are generally treated as random noise and often ascribed
 279 to confounding ‘volatile’ factors, such as participants’ momentary alertness level, here we specifically
 280 tested the functional relevance of such differences. Importantly, the observed effects cannot be
 281 accounted for by a spurious association with volatile confounds, since the electrophysiological and
 282 behavioural assessments took place in different contexts, separated by a day or more. Furthermore, we
 283 removed the potential confounding effects of a substantial array of cognitive and demographic factors,
 284 ensuring that the results we report are specific to the relevant behavioural domain, namely speech
 285 processing. In attempting to remove confounding factors from the data we also revealed how WIN
 286 recognition performance is associated with a number of indices (Fig. 1). Although a comprehensive
 287 discussion of such associations is beyond the scope of the present report, one that is arguably of special
 288 interest is that with verbal working memory (vWM). vWM has long been implicated in speech-in-noise
 289 recognition (Rönnberg et al., 2013), though a recent meta-analysis has concluded that this relation only
 290 holds true in the context of aging and/or hearing impairment (Füllgrabe & Rosen, 2016). Here,
 291 intriguingly, we observed this association in a sample of young normally-hearing participants.
 292 The results do not appear to shadow the left-right asymmetries of the AST, whereby LH auditory regions
 293 are posited to express relatively more 20-50Hz activity than RH auditory areas that express greater
 294 lower-frequency power in response to speech input. Although potentially surprising at first glance, the

AST describes responses to speech input, without making any specific predictions about the system at rest, beyond the implication that it is tuned to engage with acoustic information at the proposed timescales. The spatial distribution of the present results seems to indicate that individual differences in WIN performance relate to baseline excitability levels of a number of non-primary areas in the LH known to support speech recognition that are involved in the processing (left posterior STG/STS) of phonological information and its integration with lexical (left posterior/middle MTG) information, as well as with somatosensory input from other modalities (left IPL and visual association areas; Friederici, 2012; Hickok & Poeppel, 2007). Thus, we suggest that increases in spectrally- and topographically-specific MEG power at rest, by determining a suitable context in which relevant acoustic features (i.e., cues to phonemic identity) are processed, are associated with better WIN recognition abilities.

This proposal is consistent with a number of lines of evidence. The locus of the LH high- β peak is consistent with the region in which categorical phoneme perception has been demonstrated in fMRI (e.g., Specht, Baumgartner, Stadler, Hugdahl, & Pollmann, 2014; see Turkeltaub & Branch Coslett, 2010 for a review). Evidence from intracranial recordings also supports this. For example, Chang and colleagues (2010) carried out intracranial recordings of STG responses to synthesised phonemic continua and found neural populations in pSTG responding to phonemic cues important for phoneme recognition. In addition, they observed populations of neurons responding selectively and categorically to single phonemes, providing a strong physiological correspondence to the behavioural categorical perception phenomenon. A further study (Mesgarani, Cheung, Johnson, & Chang, 2014) has shown that neuronal populations discretely responding to phoneme categories are hierarchically clustered in a way that is strikingly similar to the traditional clustering of phonemes performed by phoneticians and linguists. Mesgarani and colleagues (2014) conclude that selectivity is determined primarily by acoustic cues for manner and secondarily by place of articulation (and, in general, by articulatory properties). Further, we observe areas of significant WIN recognition – RS power association more anteriorly along

the left STG and MTG. These areas have been implicated by a number of studies in the representing phonemes with higher specificity and invariance (Ashtari et al., 2004; DeWitt & Rauschecker, 2012; Liebenenthal, Binder, Spitzer, Possing, & Medler, 2005).

Brain-behaviour relationships observed in this study were confined to two neighbouring frequency bands (21-29 and 30-40Hz). Different lines of inquiry indicate that neural activity within this range of the spectrum is important for the parsing and processing of acoustical information on short time scales relevant for phoneme recognition, i.e., phonetic features. Among the work supporting this hypothesis, relatively strong evidence comes from a growing body of research on exogenous modulation of neural excitability. Recent studies using transcranial alternating current stimulation (tACS) have begun to provide causal evidence for the role of oscillations in this frequency range for phoneme perception. The oscillatory current produced by tACS is assumed to instantaneously synchronize (i.e., to entrain) the firing in the targeted neuronal populations, enhancing oscillatory power at the stimulation frequency (Helfrich et al., 2014). A recent study using tACS reported the induction of phoneme recognition deficits in healthy participants as a result of applying a 40Hz current to auditory areas (Rufener, Zaehle, Oechslin, & Meyer, 2016). In a separate study, Rufener, Zaehle and colleagues (2016) found that applying 40Hz stimulation to the bilateral auditory cortex reduced the rate of perceptual learning during a phoneme categorisation task, while applying 6Hz tACS stimulation did not affect perceptual learning. Importantly, whilst this result was replicated in a comparable sample of young participants (20-35 years), it was shown that perceptual learning of older participants (60-75 years) was enhanced, rather than hindered, by 40Hz stimulation and the presumed tACS-induced enhancement of 40Hz activity, with 6Hz stimulation again having no significant effect (Rufener, Oechslin, Zaehle, & Meyer, 2016).

Intriguingly, Rufener and colleagues suggest that the effect of perturbing low- γ activity may depend on (i.e., interact with) its 'pre-existing' (i.e., RS) level.

The idea that there may be such a thing as an optimal resting-state level for phoneme processing is further supported by experiments on developmental dyslexia (DD). DD is a common disability defined as sub-normal acquisition of reading skills and phonological abilities within the context of otherwise normal hearing and cognitive abilities. Rufener and colleagues (Rufener, Krauel, Meyer, Heinze, & Zaehle, 2019) showed that 40Hz tACS stimulation over the bilateral auditory cortex improved phoneme-categorisation accuracy in a sample of patients suffering from DD. Thus, by altering the putatively optimal balance of synchronous endogenous activity in healthy individuals unaffected by phonological deficits, sampling of rapid acoustic events is altered and performance is worsened. In contrast, when the equilibrium of oscillatory activity is sub-optimal, as might be the case in the context of healthy aging (Voytek et al., 2015) and DD (Hancock, Pugh, & Hoeft, 2017), abnormal, or sub-optimal, temporal sampling is remediated by the external stimulation, and performance improves. Taken together, evidence from these tACS studies strongly supports a causal involvement of low- γ activity in the rapid auditory processing hypothesised to be essential for phoneme extraction and identification.

A large body of evidence suggests that the phonological deficits that characterise DD may arise from abnormal sampling of the speech stream into the short time windows relevant for the processing of phonetic cues (Chobert, François, Habib, & Besson, 2012; Gaab, Gabrieli, Deutsch, Tallal, & Temple, 2007; Raschle, Stering, Meissner, & Gaab, 2014; Snowling, 1998). Consequently, DD is increasingly characterised as a disruption of rapid auditory processing (RAP). Lehongre and colleagues (Lehongre et al., 2011) tested the auditory steady state response (ASSR) of individuals affected by DD and a group of controls. ASSR reflects an intrinsic and stable property of the brain that is relevant for auditory processing (Baltus & Herrmann, 2015). Lehongre and colleagues (2011) found that the magnitude of left lateralised ASSR to 30Hz amplitude-modulated stimuli was reduced compared to controls, and that the magnitude of the ASSR in planum temporale at 30Hz in both DD and control participants predicted performance on phonological tasks. They take this to be a reflection of an intrinsic property of the

auditory system and conclude that an abnormal oscillatory rhythm in left auditory areas in the range 25-35Hz is responsible for DD. This demonstrates the relevance of this frequency range at this cortical area, for speech perception, consistent with our finding that RS activity in this frequency region at this anatomical locus predicts WIN performance. Further, deviance from normal ASSRs in the 25-35Hz range were observed by Lehongre and collaborators also in the left prefrontal cortex and in the right posterior superior temporal cortex, showing a high spatial similarity with regions that were correlated with WIN recognition abilities in our sample of healthy participants. Unfortunately, the boundaries of this frequency range exactly matches the centre of two different frequency bands defined in this study (21-29Hz and 30-40Hz, respectively), slightly complicating the comparison. Nevertheless, the ASSR is known to peak higher in the RH than LH (Lehongre et al., 2011; Ross, Herdman, & Pantev, 2005), and the effect we observe may be related to this asymmetry. Indeed, it is possible that our results indicate that higher power at the peak ASSR frequency of the auditory system at rest is beneficial for speech perception. Under the assumption that the human auditory system has co-evolved with speech and is thus highly tuned to the acoustic properties of the latter, it may not be too much of a stretch to suggest that higher resting-state activity at the peak of the local neural tuning may provide a superior neural context for speech stimulus processing, underpinning improved speech in noise perception.

The present study is, perforce, subject to a number of limitations. One issue is the task that was used to evaluate speech in noise perception, namely the Words-In-Noise test. This presents participants only with a series of unconnected monosyllabic words. Use of such a set precluded investigation of another oscillatory component that has recently been tied to speech comprehension, namely the θ band (Ding, Melloni, Zhang, Tian, & Poeppel, 2015; Peelle & Davis, 2012). According to a number of reports and the predictions of the AST, θ underpins the syllabic parsing based on envelope cues, which are neither relevant nor present in the WIN. Further investigations of individual differences in performance on noisy

connected speech materials would be necessary to evaluate whether RS θ may also contribute to the comprehension of acoustically challenging speech under slightly more ecologically valid conditions.

A further limitation relates to the fact that audiometry tests such as Pure Tone Audiometry (PTA) or tests of speech recognition in quiet were not part of the battery of behavioural assessments which we used to deconfound the WIN score. As a consequence, we cannot rule out that the effects we observed relate to the perceptual bases of speech recognition, or even hearing abilities per se. Nevertheless, most tests of speech-in-noise recognition tests, including the WIN test one used here, are based on a dual-component model of hearing (dis)ability: ‘signal amplification/attenuation’ (or audibility) refers to pure-tone sensitivity, whilst ‘signal filtering/distortion’ refers to the ability to understand speech in a noisy background (Plomp, 1986). These two functions are thought to be independent, or to be very weakly coupled at best. Indeed, although a few studies did report a relationship between pure-tone audiometry (PTA) and speech-in-noise performance (Lutman, 1991; Tschopp & Züst, 1994), the majority of the reports confirmed the dissociation between the two components (e.g., Blandy & Lutman, 2005; Dubno, Dirks, & Morgan, 1984; Duquesnoy, 1983; Jerger, 1992). One recent study reported that – when controlling for age – whilst PTA predicted speech recognition in quiet, these two measures were not associated with speech-in-noise recognition in neither normally-hearing nor hearing-impaired individuals (Vermiglio, Soli, Freed, & Fisher, 2012). Similarly and most importantly, the WIN test itself was shown to be independent from PTA as well as from speech recognition in quiet in elderly with mild-to-moderate hearing loss (Wilson et al., 2005), suggesting that threshold elevation in terms of signal-to-noise ratio, rather than signal attenuation, is what is chiefly assessed by this test. Thus, we believe that the associations between RS power and WIN recognition insofar described relate specifically to the perceptual foundations of resilience to noise-induced breakdown of speech intelligibility.

5. Conclusion

We have observed that analysis of spectrally-resolved RS-electrophysiology can provide valuable insights into the spatial and spectral properties of cerebral systems that are specific to WIN recognition. In this regard, the present results are consistent with the growing body of research indicating that the interactions between resting and evoked activity need to be better characterised in order to obtain a more complete and accurate account of cerebral functioning. In particular, beyond advancing our understanding of properties intrinsic to the brain that determine speech comprehension, a number of implications arise from this investigation. First, it suggests, together with a number of studies presented above, that altering resting oscillatory activity associated with RAP may constitute a viable approach for overcoming phonological processing deficits that arise from sub-optimal resting-state oscillatory activity patterns. This has already been shown to be the case within the realm of non-invasive electrical stimulation, but other interventions aimed at altering the balance of endogenous oscillatory activity associated with phonological processing can be conceived, such as EEG-informed neurofeedback, or closed-loop neurostimulation, targeting the spectral and spatial regions highlighted here. Furthermore, since the affordances of such interventions are inevitably tightly linked to pre-intervention activity levels, characterisation of RS activity in the normal population and in populations of patients affected by phonological impairments is a necessary step for the development of effective interventions. Thus, the scope of the analysis of neural correlates of RS power extends well beyond fundamental research and has important implications for applied research into how to support and enhance the auditory brain's resilience in the face of noisy signals.

Statement of Significance

We show that resting-state power, measured by MEG, in auditory cortices and left perisylvian areas is predictive of individual differences in speech in noise recognition performance. Intrinsic brain properties

indexed by resting-state activity are behaviourally relevant, and provide further insight into the neural substrates of speech in noise processing capacity.

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Declaration of Interests:

The authors declare no competing interests.

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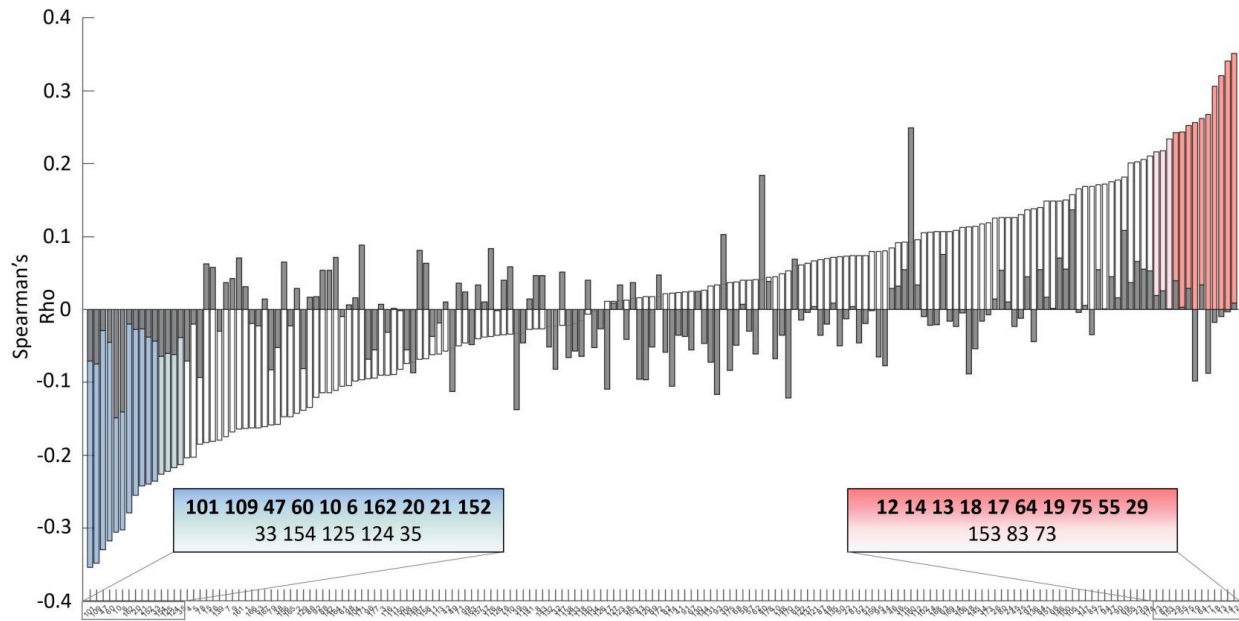


Figure 1. Effect of deconfounding WIN scores on the association with confounds. X-axis represents confounds (one per bar, sorted ascendingly by correlation coefficient; numbers represent the confound label 'ID_out' in Appendix) and Y-axis represents the correlation coefficient (Spearman's Rho) between WIN SNR and each confound. Color-codes: white bars = non-significant correlations between original (non-deconfounded) WIN SNR scores and confound; light-blue bars = significant (p < .05, uncorrected) negative correlations between original WIN SNR scores and confound; dark-blue bars = significant (p < .05, FDR-corrected) negative correlations between original WIN SNR scores and confound; pink bars = significant (p < .05, uncorrected) positive correlations between original WIN SNR scores and confound; red bars = significant (p < .05, FDR-corrected) positive correlations between original WIN SNR scores and confound; overlaid grey bars = (non-significant) correlations between deconfounded WIN SNR and confound. Numbers in bold within boxes represent the confound label of significant FDR-corrected WIN-confound correlations, whilst the others represent the confound label of significant non-corrected WIN-confound correlations.

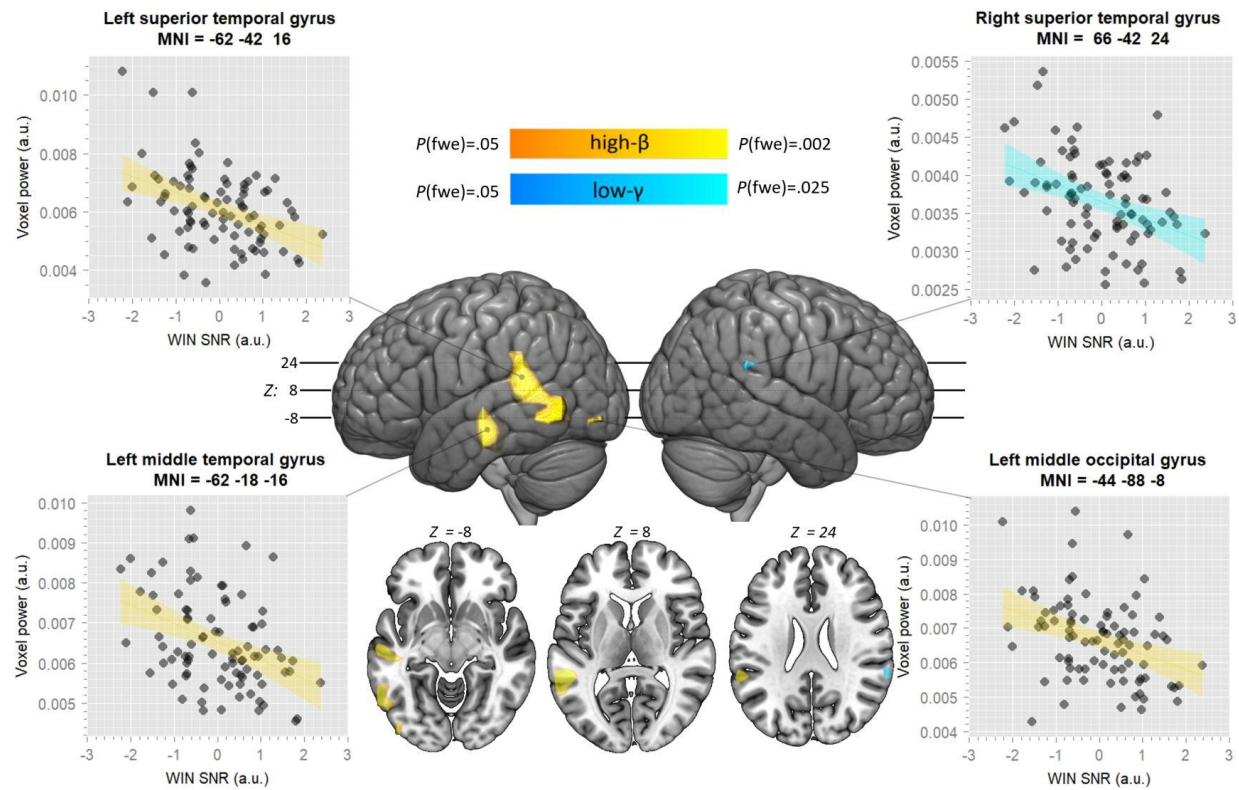


Figure 2. Surface rendering and axial slices of significant correlations between WIN SNR and voxel power. Significant correlations in the high- β band are represented in warm colours, whilst significant associations in the low- γ band are represented in cold colours. The scatterplots represent the association at each of four representative voxels by means of a regression line with standard error bounds.

685 Table 1. Criteria for the selection of subject measures entering the PCA (adapted from Smith et al., 2015).

Criterion	Formal requirement
Subject measure data need to have enough variability	1. Standard deviation (SD) > 0
	2. At least 49 valid subject scores
	3. The number of values in the largest group of unique values must not exceed 80% of the total number of valid values
Subject measure data need to have excessively high leverage points	4. If x_s is a subject measure value for subject s , and $y_s = (x_s - \text{median}(x_s))^2$, the subject measure must not contain any x_s for which $\max(y_s) > 100 \times \text{mean}(y_s)$.

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Table 2. Summary of loci of significant correlations between RS brain activity and WIN recognition. Anatomical labels were obtained using in-house routines to assign identity according to the nearest labelled coordinate in the AAL template (Tzourio-Mazoyer et al., 2002), Brodmann area labels were extracted from the BA template provided with MRICron (<https://www.nitrc.org/projects/mricron>). More than one peak per cluster is reported if peaks are at least 24mm apart.

	Cluster ID	N vox	AAL Label	BA	x,y,z	t	p
High-β	1	24	Left superior temporal gyrus	BA42	-62,-42,16	2.602	0.002
			Left middle temporal gyrus	BA37	-62,-66,0	2.06	0.009
	2	15	Left middle temporal gyrus	BA21	-62,-18,-16	2.102	0.008
	3	2	Left middle occipital gyrus	BA18	-46,-90,-8	1.556	0.028
	4	1	Left inferior parietal gyrus	BA40	-46,-58,56	1.383	0.041
Low-γ	1	3	Right superior temporal gyrus	BA48	66,-42,24	1.602	0.025

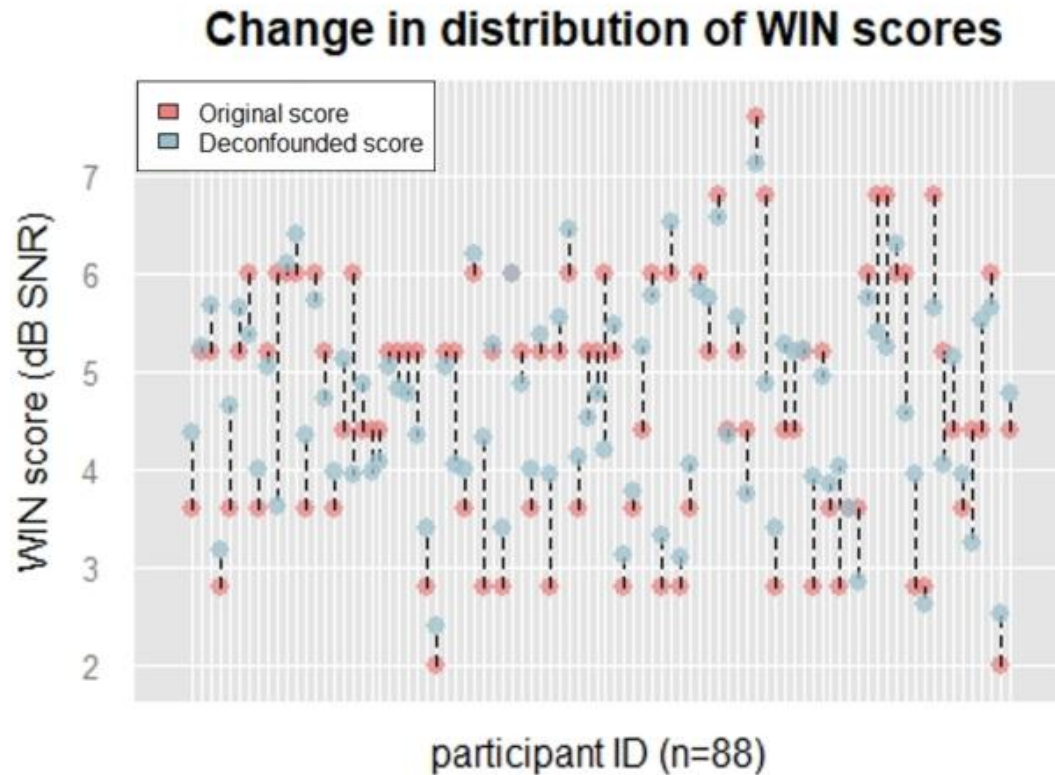


Figure S1. Change induced by deconfounding WIN on individual dB SNR scores. X-axis = participant ID; y-axis = WIN score in dB SNR; blue dots = original WIN scores; red dots = deconfounded WIN scores; dashed lines = change in WIN score associated with deconfounding procedure. Note: original WIN score was standardized to mean = 0 and SD = 1 before deconfounding; similarly, the deconfounded scores used to predict voxelwise power in the regression analysis were also standardized. Non-standardized scores are only used here for display purposes.



Figure S2. Effect of deconfounding WIN on the distribution of scores. Red dots represent the original scores (in dB SNR) of the corresponding subset of participants and blue dots above and below each original score represent each newly-deconfounded WIN score for each score-group. Performance of participants in our sample spanned eight dB SNR levels before deconfounding. The reduction in variance resulting from deconfounding is apparent in the way scores representing relatively better performance (2-4.4 dB SNR) increased on average (i.e., they represent relatively worse performance) and, vice versa, scores representing relatively worse performance (5.2-7.6 dB SNR) decreased on average (i.e., they represent relatively better performance).

Appendix. List and description of confounds.

ID in = identifier of the confounds before the selection procedure (see Table 1 for the selection criteria).

Formal database name = column headers of the “restricted” and “open access” csv files available here: <http://humanconnectome.org/data>.

Full display name, Category, Assessment = description of the confounds from the “data dictionary” csv file available here:

https://wiki.humanconnectome.org/display/PublicData/HCP+Data+Dictionary+Public-+Updated+for+the+1200+Subject+Release?preview=/53444663/113377284/HCP_S1200_DataDictionary_April_20_2018.csv

r, *p(unc.)*, *p(FDR)* = correlation coefficient, uncorrected p-value and FDR-corrected p-value of the correlation (Spearman’s rho) between the confound and the original (non-deconfounded) WIN SNR score. For three measures, these values are not available because the correlation could not have been computed as there was no variation of observations around the mean (same score for all f the participants).

I = indicates whether the measure has been included in the PCA (‘y’) or not (‘n’).

ID out = identifier of the selected confounds (those that entered the PCA).

ID in	Formal database name	Full display name	Category	Assessment	r	p (unc.)	p (FDR)	I	ID out
1	PicVocab_Unadj	NIH Toolbox Picture Vocabulary Test: Unadjusted Scale Score	Cognition	Language/Vocabulary Comprehension (Picture Vocabulary)	-0.163	0.129	0.171	y	1
2	PicVocab_AgeAdj	NIH Toolbox Picture Vocabulary Test: Age-Adjusted Scale Score	Cognition	Language/Vocabulary Comprehension (Picture Vocabulary)	-0.142	0.186	0.195	y	2
3	PMAT24_A_CR	Penn Progressive Matrices: Number of Correct Responses (PMAT24_A_CR)	Cognition	Fluid Intelligence (Penn Progressive Matrices)	-0.09	0.403	0.272	y	3
4	DDisc_AUC_200	Delay Discounting: Area Under the Curve for Discounting of \$200 (DDisc_AUC_200)	Cognition	Self-regulation/Impulsivity (Delay Discounting)	-0.204	0.057	0.117	y	4
5	THC	Positive test for THC	Substance Use	Breathalyzer and Drug Test Results	0.044	0.681	0.339	n	-
6	LifeSatisf_Unadj	NIH Toolbox General Life Satisfaction Survey: Unadjusted Scale Score	Emotion	Psychological Well-being (Positive Affect, Life Satisfaction, Meaning and Purpose)	-0.202	0.058	0.114	y	5
7	ListSort_AgeAdj	NIH Toolbox List Sorting Working Memory Test: Age-Adjusted Scale Score	Cognition	Working Memory (List Sorting)	-0.302	0.004	0.031	y	6
8	ReadEng_Unadj	NIH Toolbox Oral Reading Recognition Test: Unadjusted Scale Score	Cognition	Language/Reading Decoding (Oral Reading Recognition)	-0.174	0.105	0.162	y	7
9	SCPT_SPEC	Short Penn Continuous Performance Test: Specificity = SCPT_TN/(SCPT_TN + SCPT_FP) (SCPT_SPEC)	Cognition	Sustained Attention (Short Penn Continuous Performance Test)	-0.027	0.805	0.347	y	8

10	ReadEng_AgeAdj	NIH Toolbox Oral Reading Recognition Test: Age-Adjusted Scale Score	Cognition	Language/Reading Decoding (Oral Reading Recognition)	-0.168	0.118	0.169	y	9
11	ListSort_Unadj	NIH Toolbox List Sorting Working Memory Test: Unadjusted Scale Score	Cognition	Working Memory (List Sorting)	-0.306	0.004	0.031	y	10
12	DDisc_AUC_40K	Delay Discounting: Area Under the Curve for Discounting of \$40,000 (DDisc_AUC_40K)	Cognition	Self-regulation/Impulsivity (Delay Discounting)	-0.062	0.568	0.309	y	11
13	Avg_Weekday_Any_Tobacco_7days	Avg total weekday ANY TOBACCO per day in past 7 days	Substance Use	Tobacco Use 7-Day Retrospective	0.351	0.001	0.019	y	12
14	Num_Days_Used_Any_Tobacco_7days	Number days smoked/used ANY TOBACCO in past 7 days	Substance Use	Tobacco Use 7-Day Retrospective	0.321	0.003	0.024	y	13
15	Total_Any_Tobacco_7days	Total times used/smoked ANY TOBACCO in past 7 days	Substance Use	Tobacco Use 7-Day Retrospective	0.341	0.002	0.022	y	14
16	PicSeq_AgeAdj	NIH Toolbox Picture Sequence Memory Test: Age-Adjusted Scale Score	Cognition	Episodic Memory (Picture Sequence Memory)	-0.182	0.089	0.157	y	15
17	FamHist_Fath_DrgAlc	Father Drug or Alcohol Problems	Health and Family History	Family History of Psychiatric and Neurologic Disorders	-0.036	0.739	0.34	n	-
18	PicSeq_Unadj	NIH Toolbox Picture Sequence Memory Test: Unadjusted Scale Score	Cognition	Episodic Memory (Picture Sequence Memory)	-0.181	0.091	0.154	y	16
19	Avg_Weekday_Cigarettes_7days	Avg total weekday ANY TOBACCO per day in past 7 days	Substance Use	Tobacco Use 7-Day Retrospective	0.268	0.014	0.073	y	17
20	Avg_Weekend_Any_Tobacco_7days	Avg total weekend ANY TOBACCO per day in past 7 days	Substance Use	Tobacco Use 7-Day Retrospective	0.307	0.005	0.031	y	18
21	Total_Cigarettes_7days	Total # CIGARETTES in past 7 days	Substance Use	Tobacco Use 7-Day Retrospective	0.256	0.019	0.076	y	19
22	Dexterity_AgeAdj	NIH Toolbox 9-hole Pegboard Dexterity Test : Unadjusted Scale Score	Motor	Dexterity (9-hole Pegboard)	-0.255	0.017	0.082	y	20
23	Avg_Weekend_Cigarettes_7days	Avg weekend CIGARETTES per day in past 7 days	Substance Use	Tobacco Use 7-Day Retrospective	0.261	0.017	0.077	n	-
24	Dexterity_Unadj	NIH Toolbox 9-hole Pegboard Dexterity Test : Age-Adjusted Scale Score	Motor	Dexterity (9-hole Pegboard)	-0.242	0.023	0.082	y	21
25	Times_Used_Any_Tobacco_Today	Times used/smoked ANY TOBACCO TODAY	Substance Use	Tobacco Use 7-Day Retrospective	0.405	0	0.01	n	-
26	PSQI_Score	Sleep (Pittsburgh Sleep Questionnaire) Total Score	Alertness	Sleep (Pittsburgh Sleep Questionnaire)	0.073	0.496	0.297	y	22
27	AngAggr_Unadj	NIH Toolbox Anger-Physical Aggression Survey: Unadjusted Scale Score	Emotion	Negative Affect (Sadness, Fear, Anger)	0.203	0.058	0.116	y	23
28	Taste_AgeAdj	NIH Toolbox Regional Taste Intensity Age 12+ Age-Adjusted Scale Score	Sensory	Taste (Taste Intensity Test)	0.126	0.241	0.224	y	24
29	ASR_Rule_Raw	ASR Rule Breaking Behavior Raw Score (ASR_Rule_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.13	0.227	0.218	y	25
30	Taste_Unadj	NIH Toolbox Regional Taste Intensity Age 12+ Unadjusted Scale Score	Sensory	Taste (Taste Intensity Test)	0.125	0.244	0.221	y	26

31	ASR_Thot_Raw	ASR Thought Problems Raw Score (ASR_Thot_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.175	0.103	0.163	y	27
32	EVA_Denom	EVA score - Denominator	Sensory	Vision (EVA Scores and Farnsworth Test)	0.113	0.293	0.245	y	28
33	SSAGA_TB_Still_Smoking	Whether age last smoked is current age	Substance Use	Tobacco Use and Dependence	0.243	0.023	0.084	y	29
34	FamHist_Fath_None	Father None of the Above	Health and Family History	Family History of Psychiatric and Neurologic Disorders	0.034	0.752	0.34	y	30
35	ASR_Thot_Pct	ASR Thought Problems Gender and Age Adjusted T-score (ASR_Thot_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.165	0.123	0.173	y	31
36	PercStress_Unadj	NIH Toolbox Perceived Stress Survey: Unadjusted Scale Score	Emotion	Stress and Self Efficacy (Perceived Stress, Self-Efficacy)	-0.023	0.834	0.342	y	32
37	ProcSpeed_AgeAdj	NIH Toolbox Pattern Comparison Processing Speed Test: Age-Adjusted Scale Score	Cognition	Processing Speed (Pattern Completion Processing Speed)	-0.235	0.027	0.088	y	33
38	ASR_Rule_Pct	ASR Rule Breaking Behavior Gender and Age Adjusted T-score (ASR_Rule_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.117	0.276	0.241	y	34
39	ProcSpeed_Unadj	NIH Toolbox Pattern Comparison Processing Speed Test: Unadjusted Scale Score	Cognition	Processing Speed (Pattern Completion Processing Speed)	-0.213	0.046	0.115	y	35
40	DSM_Antis_Raw	ASR DSM Antisocial Personality Problems Raw Score (DSM_Antis_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.092	0.396	0.269	y	36
41	ER40_CR	Penn Emotion Recognition Test: Number of Correct Responses (ER40_CR)	Emotion	Emotion Recognition (Penn Emotion Recognition Test)	-0.038	0.728	0.342	y	37
42	NEOFAC_A	NEO-FFI Agreeableness (NEOFAC_A)	Personality	Five Factor Model (NEO-FFI) Factor Summary Scores	-0.158	0.143	0.176	y	38
43	ASR_Crit_Raw	ASR Critical Items Raw Score (ASR_Crit_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	-0.033	0.762	0.338	y	39
44	VSPLIT_TC	Variable Short Penn Line Orientation: Total Number Correct (VSPLIT_TC)	Cognition	Spatial Orientation (Variable Short Penn Line Orientation Test)	0.041	0.705	0.344	y	40
45	NEOFAC_O	NEO-FFI Openness to Experience (NEOFAC_O)	Personality	Five Factor Model (NEO-FFI) Factor Summary Scores	0.023	0.83	0.342	y	41
46	ER40ANG	Penn Emotion Recognition Test: Number of Correct Anger Identifications (ER40ANG)	Emotion	Emotion Recognition (Penn Emotion Recognition Test)	-0.057	0.598	0.312	y	42
47	VSPLIT_OFF	Variable Short Penn Line Orientation: Total Positions Off for All Trials (VSPLIT_OFF)	Cognition	Spatial Orientation (Variable Short Penn Line Orientation Test)	0.016	0.883	0.345	y	43
48	SSAGA_Times_Used	Times used stimulants	Substance Use	Illicit Drug Use	-0.102	0.344	0.253	n	-
49	ASR_Soma_Pct	ASR Somatic Complaints Gender and Age Adjusted T-score (ASR_Soma_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.081	0.455	0.291	y	44
50	SSAGA_Mj_Times_Used	Times used marijuana	Substance Use	Marijuana Use and Dependence	0.072	0.503	0.167	y	45

51	DSM_Antis_Pct	ASR DSM Antisocial Personality Problems Gender and Age Adjusted T-score (DSM_Antis_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.085	0.433	0.284	y	46
52	CardSort_AgeAdj	NIH Toolbox Dimensional Change Card Sort Test: Age-Adjusted Scale Score	Cognition	Executive Function/Cognitive Flexibility (Dimensional Change Card Sort)	-0.33	0.002	0.021	y	47
53	ASR_Extn_Raw	ASR Internalizing Gender and Age Adjusted T-score (ASR_Intn_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.07	0.519	0.298	y	48
54	ASR_Oth_Raw	ASR Other Problems Raw Score (ASR_Oth_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	-0.053	0.624	0.321	y	49
55	ASR_Totp_T	ASR Total Problems Gender and Age Adjusted T-score (ASR_Totp_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.072	0.503	0.296	y	50
56	ASR_Extn_T	ASR Externalizing Gender and Age Adjusted T-score (ASR_Computed_Externalizing_Adjusted_T) (ASR_Extn_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.074	0.493	0.305	y	51
57	ASR_Totp_Raw	ASR Total Problems Raw Score (ASR_Totp_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.074	0.494	0.3	y	52
58	EmotSupp_Unadj	NIH Toolbox Emotional Support Survey: Unadjusted Scale Score	Emotion	Social Relationships (Social Support, Companionship, Social Distress, Positive Social Development)	-0.162	0.131	0.167	y	53
59	DSM_Anxi_Pct	ASR DSM Anxiety Problems Gender and Age Adjusted T-score (DSM_Anxi_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.109	0.313	0.253	y	54
60	PercReject_Unadj	NIH Toolbox Perceived Rejection Survey: Unadjusted Scale Score	Emotion	Social Relationships (Social Support, Companionship, Social Distress, Positive Social Development)	0.244	0.022	0.087	y	55
61	ER40NOE	Penn Emotion Recognition Test: Number of Correct Neutral Identifications (ER40NOE)	Emotion	Emotion Recognition (Penn Emotion Recognition Test)	0.04	0.712	0.339	y	56
62	DSM_Anxi_Raw	ASR DSM Anxiety Problems Raw Score (DSM_Anxi_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.04	0.709	0.342	y	57
63	ASR_TAO_Sum	ASR Sum of Thought, Attention, and Other Problems Raw Score (ASR_TAO_Sum)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.013	0.904	0.347	y	58
64	SSAGA_TB_Smokin_g_History	Smoking history	Substance Use	Tobacco Use and Dependence	0.206	0.054	0.122	y	59
65	CardSort_Unadj	NIH Toolbox Dimensional Change Card Sort Test: Unadjusted Scale Score	Cognition	Executive Function/Cognitive Flexibility (Dimensional Change Card Sort)	-0.317	0.003	0.028	y	60
66	PosAffect_Unadj	NIH Toolbox Positive Affect Survey: Unadjusted Scale Score	Emotion	Psychological Well-being (Positive Affect, Life Satisfaction, Meaning and Purpose)	-0.106	0.327	0.253	y	61

67	SSAGA_Childhood Conduct	Childhood Conduct Problems	Psychiatric and Life Function	Psychiatric History	0.041	0.707	0.343	y	62
68	Odor_AgeAdj	NIH Toolbox Odor Identification Age 3+ Age-Adjusted Scale Score	Sensory	Olfaction (Odor Identification Test)	0.107	0.321	0.254	y	63
69	ASR_Witd_Raw	ASR Withdrawn Raw Score (ASR_Witd_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.262	0.014	0.078	y	64
70	SSAGA_Alc_Hvy_Frq_Drk	Frequency drunk in heaviest 12-month period	Substance Use	Alcohol Use and Dependence	0.061	0.586	0.31	y	65
71	ASR_Soma_Raw	ASR Somatic Complaints Raw Score (ASR_Soma_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.149	0.166	0.187	y	66
72	DSM_Depr_Pct	ASR DSM Depressive Problems Gender and Age Adjusted T-score (DSM_Depr_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.025	0.82	0.346	y	67
73	ASR_Aggr_Pct	ASR Aggressive Behavior Gender and Age Adjusted T-score (ASR_Aggr_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.038	0.728	0.344	y	68
74	SSAGA_Alc_12_Max_Drinks	Max drinks in a single day in past 12 months	Substance Use	Alcohol Use and Dependence	0.182	0.1	0.161	y	69
75	DSM_Depr_Raw	ASR DSM Depressive Problems Raw Score (DSM_Depr_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.045	0.676	0.341	y	70
76	Mars_Final	Mars Final Contrast Sensitivity Score	Sensory	Contrast Sensitivity (Mars Contrast Sensitivity)	-0.035	0.747	0.194	y	71
77	PercHostil_Unadj	NIH Toolbox Perceived Hostility Survey: Unadjusted Scale Score	Emotion	Social Relationships (Social Support, Companionship, Social Distress, Positive Social Development)	0.171	0.11	0.163	y	72
78	DSM_Somp_Pct	ASR DSM Somatic Problems Gender and Age Adjusted T-score (DSM_Somp_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.216	0.043	0.109	y	73
79	SSAGA_Alc_Age_1st_Use	Age at first alcohol use	Substance Use	Alcohol Use and Dependence	0.106	0.339	0.254	y	74
80	ASR_Witd_Pct	ASR Withdrawn Gender and Age Adjusted T-score (ASR_Witd_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.253	0.018	0.077	y	75
81	IWRD_TOT	Penn Word Memory Test: Total Number of Correct Responses (IWRD_TOT)	Cognition	Verbal Episodic Memory (Penn Word Memory Test)	-0.035	0.747	0.342	y	76
82	PainInterf_Tscore	NIH Toolbox Pain Interference Survey Age 18+: T-score	Sensory	Pain (Pain Intensity and Interference Surveys)	0.011	0.919	0.344	y	77
83	MMSE_Score	Mini Mental Status Exam Total Score	Alertness	Cognitive Status (Mini Mental Status Exam)	-0.185	0.084	0.153	y	78
84	SSAGA_Alc_12_Frq_Drk	Frequency drunk in past 12 months	Substance Use	Alcohol Use and Dependence	-0.159	0.152	0.185	y	79
85	Odor_Unadj	NIH Toolbox Odor Identification Age 3+ Unadjusted Scale Score	Sensory	Olfaction (Odor Identification Test)	0.126	0.242	0.221	y	80

86	SSAGA_Alc_D4_Ab_Sx	DSM4 Alcohol Abuse number of symptoms	Substance Use	Alcohol Use and Dependence	0.06	0.58	0.312	n	-
87	SSAGA_Mj_Use	Ever used marijuana?	Substance Use	Marijuana Use and Dependence	0.074	0.495	0.299	y	81
88	ASR_Aggr_Raw	ASR Aggressive Behavior Raw Score (ASR_Aggr_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.022	0.842	0.339	y	82
89	SSAGA_Mj_Ab_De p	DSM Marijuana Dependence	Substance Use	Marijuana Use and Dependence	0.234	0.028	0.087	n	-
90	DSM_Somp_Raw	ASR DSM Somatic Problems Raw Score (DSM_Somp_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.218	0.041	0.109	y	83
91	FearSomat_Unadj	NIH Toolbox Fear-Somatic Arousal Survey: Unadjusted Scale Score	Emotion	Negative Affect (Sadness, Fear, Anger)	0.14	0.193	0.199	y	84
92	SSAGA_Alc_12_Drinks_Per_Day	Drinks per drinking day in past 12 months	Substance Use	Alcohol Use and Dependence	0.169	0.127	0.175	y	85
93	Mars_Log_Score	Mars Contrast Sensitivity Score	Sensory	Contrast Sensitivity (Mars Contrast Sensitivity)	-0.135	0.211	0.206	y	86
94	SelfEff_Unadj	NIH Toolbox Self-Efficacy Survey: Unadjusted Scale Score	Emotion	Stress and Self Efficacy (Perceived Stress, Self-Efficacy)	0.068	0.529	0.302	y	87
95	SCPT_SEN	Short Penn Continuous Performance Test: Sensitivity = SCPT_TP/(SCPT_TP + SCPT_FN) (SCPT_SEN)	Cognition	Sustained Attention (Short Penn Continuous Performance Test)	-0.114	0.29	0.25	y	88
96	NEOFAC_N	NEO-FFI Neuroticism (NEOFAC_N)	Personality	Five Factor Model (NEO-FFI) Factor Summary Scores	0.018	0.869	0.343	y	89
97	SSAGA_Agoraphobia	Agoraphobia	Psychiatric and Life Function	Psychiatric History	0.059	0.592	0.312	n	-
98	ASR_Intn_T	ASR Internalizing Gender and Age Adjusted T-score (ASR_Intn_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.178	0.098	0.161	y	90
99	AngHostil_Unadj	NIH Toolbox Anger-Hostility Survey: Unadjusted Scale Score	Emotion	Negative Affect (Sadness, Fear, Anger)	0.024	0.826	0.346	y	91
100	Num_Days_Drank_7days	Number days drank alcohol in past 7 days	Substance Use	Alcohol Use 7-Day Retrospective	-0.121	0.269	0.24	y	92
101	SSAGA_Times_Used_Cocaine	Times used cocaine	Substance Use	Illicit Drug Use	0.009	0.935	0.348	n	-
102	Loneliness_Unadj	NIH Toolbox Loneliness Survey: Unadjusted Scale Score	Emotion	Social Relationships (Social Support, Companionship, Social Distress, Positive Social Development)	0.033	0.758	0.338	y	93
103	ASR_Intn_Raw	ASR Internalizing Raw Score (ASR_Intn_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.172	0.108	0.164	y	94
104	SSAGA_Alc_Hvy_Drinks_Per_Day	Drinks per day in heaviest 12-month period	Substance Use	Alcohol Use and Dependence	0.08	0.473	0.3	y	95
105	MeanPurp_Unadj	NIH Toolbox Meaning and Purpose Survey: Unadjusted Scale Score	Emotion	Psychological Well-being (Positive Affect, Life Satisfaction, Meaning and Purpose)	-0.095	0.378	0.27	y	96

106	DSM_Avoid_Pct	ASR DSM Avoidant Personality Problems Gender and Age Adjusted T-score (DSM_Avoid_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self- Report, Syndrome Scales and DSM- Oriented Scale)	0.137	0.203	0.201	y	97
107	NEOFAC_E	NEO-FFI Extraversion (NEOFAC_E)	Personality	Five Factor Model (NEO-FFI) Factor Summary Scores	-0.104	0.333	0.252	y	98
108	Total_Beer_Wine_Cooler_7days	Total alcoholic drinks in past 7 days (Beer/Wine Coolers)	Substance Use	Alcohol Use 7-Day Retrospective	-0.046	0.676	0.339	y	99
109	DSM_Avoid_Raw	ASR DSM Avoidant Personality Problems Raw Score (DSM_Avoid_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self- Report, Syndrome Scales and DSM- Oriented Scale)	0.15	0.162	0.185	y	100
110	Avg_Weekday_Wine_7days	Avg total weekday alcoholic drinks/day in past 7 days (Wine)	Substance Use	Alcohol Use 7-Day Retrospective	0.067	0.546	0.302	n	-
111	Flanker_AgeAdj	NIH Toolbox Flanker Inhibitory Control and Attention Test: Age-Adjusted Scale Score	Cognition	Executive Function/Inhibition (Flanker Task)	-0.354	0.001	0.027	y	101
112	ASR_Anxd_Pct	ASR Anxious/Depressed Gender and Age Adjusted T-score (ASR_Anxd_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self- Report, Syndrome Scales and DSM- Oriented Scale)	0.105	0.329	0.252	y	102
113	Avg_Weekend_Beer_Wine_Cooler_7days	Avg total weekend alcoholic drinks/day in past 7 days (Beer/Wine Coolers)	Substance Use	Alcohol Use 7-Day Retrospective	0.016	0.888	0.345	y	103
114	SSAGA_Alc_D4_Ab_Dx	DSM4 Alcohol Abuse Criteria Met	Substance Use	Alcohol Use and Dependence	-0.003	0.981	0.36	n	-
115	Total_Drinks_7days	Total drinks in past 7 days	Substance Use	Alcohol Use 7-Day Retrospective	-0.098	0.374	0.272	y	104
116	SSAGA_Alc_Hvy_Max_Drinks	Lifetime max drinks in single day	Substance Use	Alcohol Use and Dependence	0.157	0.155	0.18	y	105
117	FearAffect_Unadj	NIH Toolbox Fear-Affect Survey: Unadjusted Scale Score	Emotion	Negative Affect (Sadness, Fear, Anger)	0.113	0.295	0.243	y	106
118	Total_Wine_7days	Total alcoholic drinks in past 7 days (Wine)	Substance Use	Alcohol Use 7-Day Retrospective	0.058	0.603	0.313	n	-
119	Avg_Weekday_Drinks_7days	Avg total weekday alcoholic drinks/day in past 7 days	Substance Use	Alcohol Use 7-Day Retrospective	-0.069	0.535	0.3	y	107
120	ER40SAD	Penn Emotion Recognition Test: Number of Correct Sad Identifications (ER40SAD)	Emotion	Emotion Recognition (Penn Emotion Recognition Test)	-0.074	0.493	0.302	y	108
121	Flanker_Unadj	NIH Toolbox Flanker Inhibitory Control and Attention Test: Unadjusted Scale Score	Cognition	Executive Function/Inhibition (Flanker Task)	-0.348	0.001	0.022	y	109
122	ER40FEAR	Penn Emotion Recognition Test: Number of Correct Fear Identifications (ER40FEAR)	Emotion	Emotion Recognition (Penn Emotion Recognition Test)	-0.034	0.754	0.339	y	110
123	Avg_Weekday_Beer_Wine_Cooler_7days	Avg total weekday alcoholic drinks/day in past 7 days (Beer/Wine Coolers)	Substance Use	Alcohol Use 7-Day Retrospective	-0.089	0.418	0.277	y	111
124	SSAGA_Times_Used_Illicits	Times used illicit drugs	Substance Use	Illicit Drug Use	0.096	0.375	0.27	y	112
125	Avg_Weekend_Drinks_7days	Avg total weekend alcoholic drinks/day in past 7 days	Substance Use	Alcohol Use 7-Day Retrospective	-0.061	0.582	0.31	y	113
126	SSAGA_Alc_D4_Dp_Sx	Number of DSM4 Alcohol Dependence Criteria Endorsed	Substance Use	Alcohol Use and Dependence	0.022	0.836	0.341	y	114

127	NEOFAC_C	NEO-FFI Conscientiousness (NEOFAC_C)	Personality	Five Factor Model (NEO-FFI) Factor Summary Scores	0.092	0.392	0.269	y	115
128	Total_Hard_Liquor_7days	Total alcoholic drinks in past 7 days (Hard Liquor)	Substance Use	Alcohol Use 7-Day Retrospective	-0.09	0.416	0.278	y	116
129	Correction	Eyeglass correction	Sensory	Vision (EVA Scores and Farnsworth Test)	0.104	0.34	0.252	n	-
130	SSAGA_Alc_Hvy_Frq_5plus	Frequency of drinking 5+ drinks heaviest 12-month period	Substance Use	Alcohol Use and Dependence	-0.022	0.846	0.337	y	117
131	DSM_Adh_Pct	ASR DSM AD/H Problems Gender and Age Adjusted T-score (DSM_Adh_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	-0.015	0.89	0.344	y	118
132	ASR_Attn_Pct	ASR Attention Problems Gender and Age Adjusted T-score (ASR_Attn_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	-0.032	0.766	0.336	y	119
133	VSPLOT_CRTE	Variable Short Penn Line Orientation: Median Reaction Time Divided by Expected Number of Clicks for Correct (VSPLOT_CRTE)	Cognition	Spatial Orientation (Variable Short Penn Line Orientation Test)	0.017	0.872	0.342	y	120
134	SSAGA_Depressive_Ep	Major Depressive Episode	Psychiatric and Life Function	Psychiatric History	0.184	0.09	0.156	n	-
135	AngAffect_Unadj	NIH Toolbox Anger-Affect Survey: Unadjusted Scale Score	Emotion	Negative Affect (Sadness, Fear, Anger)	0.067	0.535	0.298	y	121
136	SSAGA_PanicDisorder	Panic Disorder	Psychiatric and Life Function	Psychiatric History	0.077	0.478	0.301	n	-
137	Avg_Weekend_Hard_Liquor_7days	Avg total weekend alcoholic drinks/day in past 7 days (Hard Liquor)	Substance Use	Alcohol Use 7-Day Retrospective	-0.086	0.435	0.283	n	-
138	FamHist_Moth_Dep	Mother Depression	Health and Family History	Family History of Psychiatric and Neurologic Disorders	-0.202	0.059	0.112	n	-
139	ASR_Anxd_Raw	ASR Anxious/Depressed Raw Score (ASR_Anxd_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.061	0.571	0.309	y	122
140	SSAGA_Times_Use_d_Opiates	Times used opiates	Substance Use	Illicit Drug Use	-0.022	0.838	0.34	n	-
141	SSAGA_Times_Use_d_Sedatives	Times used sedatives	Substance Use	Illicit Drug Use	0.012	0.912	0.347	n	-
142	SSAGA_Alc_Hvy_Frq	Frequency of any alcohol use, heaviest 12-month period	Substance Use	Alcohol Use and Dependence	0.012	0.913	0.345	y	123
143	SSAGA_Alc_12_Frq_5plus	Frequency of drinking 5+ drinks in past 12 months	Substance Use	Alcohol Use and Dependence	-0.217	0.048	0.116	y	124
144	Friendship_Unadj	NIH Toolbox Friendship Survey: Unadjusted Scale Score	Emotion	Social Relationships (Social Support, Companionship, Social Distress, Positive Social Development)	-0.222	0.038	0.103	y	125
145	SSAGA_Depressive_Sx	Number Depressive Symptoms	Psychiatric and Life Function	Psychiatric History	0.001	0.994	0.363	n	-

146	ASR_Attn_Raw	ASR Attention Problems Raw Score (ASR_Attn_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.000	1	0.363	y	126
147	ASR_Intr_Raw	ASR Intrusive Raw Score (ASR_Intr_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.011	0.917	0.345	y	127
148	SSAGA_Alc_12_Frq	Frequency of any alcohol use in past 12 months	Substance Use	Alcohol Use and Dependence	-0.036	0.75	0.341	y	128
149	FamHist_Fath_Dep	Father Depression	Health and Family History	Family History of Psychiatric and Neurologic Disorders	0.024	0.827	0.345	n	-
150	InstruSupp_Unadj	NIH Toolbox Instrumental Support Survey: Unadjusted Scale Score	Emotion	Social Relationships (Social Support, Companionship, Social Distress, Positive Social Development)	-0.138	0.199	0.202	y	129
151	ASR_Intr_Pct	ASR Intrusive Gender and Age Adjusted T-score (ASR_Intr_T)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	0.025	0.819	0.347	y	130
152	SSAGA_Times_Use	Times used hallucinogens	Substance Use	Illicit Drug Use	0.073	0.498	0.295	n	-
153	Avg_Weekend_Wine_7days	Avg total weekend alcoholic drinks/day in past 7 days (Wine)	Substance Use	Alcohol Use 7-Day Retrospective	-0.013	0.907	0.347	n	-
154	FamHist_Moth_None	Mother None of the Above	Health and Family History	Family History of Psychiatric and Neurologic Disorders	0.204	0.056	0.122	n	-
155	Sadness_Unadj	NIH Toolbox Sadness Survey: Unadjusted Scale Score	Emotion	Negative Affect (Sadness, Fear, Anger)	0.032	0.764	0.337	y	131
156	DSM_Hype_Raw	ASR DSM Hyperactivity Problems Raw Score (DSM_Hype_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	-0.023	0.829	0.343	y	132
157	DSM_Adh_Raw	ASR DSM AD/H Problems Raw Score (DSM_Adh_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	-0.019	0.858	0.34	y	133
158	DSM_Inat_Raw	ASR DSM Inattention Problems Raw Score (DSM_Inat_Raw)	Psychiatric and Life Function	Life Function (Achenbach Adult Self-Report, Syndrome Scales and DSM-Oriented Scale)	-0.003	0.981	0.362	y	134
159	Height	Height	Health and Family History	Physical Health	0.072	0.508	0.294	y	135
160	Weight	Weight	Health and Family History	Physical Health	0.138	0.199	0.2	y	136
161	BPSystolic	Blood Pressure - Systolic	Health and Family History	Physical Health	0.063	0.56	0.308	y	137
162	BPDiastolic	Blood Pressure - Diastolic	Health and Family History	Physical Health	-0.021	0.844	0.338	y	138
163	HbA1C	Hemoglobin A1C (HbA1C)	Health and Family History	Physical Health	-0.179	0.153	0.183	y	139
164	FS_IntraCranial_Vol	Estimated intra-cranial volume	FreeSurfer	FreeSurfer Summary Statistics	-0.006	0.953	0.353	y	140
165	FS_BrainSeg_Vol	Brain segmentation volume	FreeSurfer	FreeSurfer Summary Statistics	-0.027	0.801	0.347	y	141

166	SCPT_TP	Short Penn Continuous Performance Test: True Positives = Sum of CPN_TP and CPL_TP (SCPT_TP)	Cognition	Sustained Attention (Short Penn Continuous Performance Test)	-0.114	0.29	0.247	y	142
167	SCPT_TN	Short Penn Continuous Performance Test: True Negatives = Sum of CPN_TN and CPL_TN (SCPT_TN)	Cognition	Sustained Attention (Short Penn Continuous Performance Test)	-0.027	0.805	0.345	y	143
168	SCPT_FP	Short Penn Continuous Performance Test: False Positives = Sum of CPN_FP and CPL_FP (SCPT_FP)	Cognition	Sustained Attention (Short Penn Continuous Performance Test)	0.027	0.805	0.343	y	144
169	SCPT_FN	Short Penn Continuous Performance Test: False Negatives = Sum of CPN_FN and CPL_FN (SCPT_FN)	Cognition	Sustained Attention (Short Penn Continuous Performance Test)	0.114	0.29	0.245	y	145
170	SCPT_TPRT	Short Penn Continuous Performance Test: Median Response Time for True Positive Responses (SCPT_TPRT)	Cognition	Sustained Attention (Short Penn Continuous Performance Test)	0.149	0.168	0.186	y	146
171	SCPT_LRNR	Short Penn Continuous Performance Test: Longest Run of Non-Responses (SCPT_LRNR)	Cognition	Sustained Attention (Short Penn Continuous Performance Test)	0.169	0.116	0.169	y	147
172	PMAT24_A_SI	Penn Progressive Matrices: Total Skipped Items (PMAT24_A_SI)	Cognition	Fluid Intelligence (Penn Progressive Matrices)	0.049	0.652	0.331	y	148
173	PMAT24_A_RTCT	Penn Progressive Matrices: Median Reaction Time for Correct Responses (PMAT24_A_RTCT)	Cognition	Fluid Intelligence (Penn Progressive Matrices)	-0.072	0.504	0.294	y	149
174	Emotion_Task_Acc	OVERALL Emotion Task accuracy	In-Scanner Task Performance	Emotion	-0.082	0.455	0.293	y	150
175	Emotion_Task_Median_RT	OVERALL Emotion Task Reaction Time	In-Scanner Task Performance	Emotion	0.148	0.173	0.186	y	151
176	Language_Task_Story_Acc	Language Task STORY accuracy	In-Scanner Task Performance	Language	-0.24	0.026	0.088	y	152
177	Language_Task_Story_Median_RT	Language Task STORY median Reaction Time	In-Scanner Task Performance	Language	0.234	0.03	0.09	y	153
178	Language_Task_Math_Acc	Language Task MATH accuracy	In-Scanner Task Performance	Language	-0.226	0.036	0.104	y	154
179	Language_Task_Math_Median_RT	Language Task MATH median Reaction Time	In-Scanner Task Performance	Language	0.201	0.063	0.117	y	155
180	Relational_Task_Acc	Relational Task OVERALL accuracy	In-Scanner Task Performance	Relational	-0.147	0.177	0.187	y	156
181	Relational_Task_Median_RT	Relational Task OVERALL Reaction Time	In-Scanner Task Performance	Relational	-0.04	0.712	0.34	y	157
182	WM_Task_Acc	Working Memory Task Overall Accuracy	In-Scanner Task Performance	Working Memory	-0.067	0.534	0.302	y	158
183	WM_Task_Median_RT	Working Memory Task Overall Reaction Time	In-Scanner Task Performance	Working Memory	0.079	0.479	0.299	y	159
184	SSAGA_Employ	Employment Status	Subject Information	Demographics	0.092	0.392	0.272	y	160

185	SSAGA_Income	Household Income	Subject Information	Demographics	-0.164	0.127	0.172	y	161
186	SSAGA_Educ	Education	Subject Information	Demographics	-0.279	0.008	0.052	y	162
187	SSAGA_InSchool	Still in School	Subject Information	Demographics	-0.044	0.686	0.339	y	163
188	SSAGA_Rlshp	Relationship Status	Subject Information	Demographics	-0.111	0.302	0.246	y	164
189	SSAGA_MOBorn	Missouri Born	Subject Information	Demographics	0.128	0.235	0.223	n	-
190	Cocaine	Positive test for Cocaine	Substance Use	Breathalyzer and Drug Test Results	NaN	NaN	NaN	n	-
191	Opiates	Positive test for Opiates	Substance Use	Breathalyzer and Drug Test Results	0.031	0.772	0.337	n	-
192	Amphetamines	Positive test for Amphetamines	Substance Use	Breathalyzer and Drug Test Results	-0.095	0.381	0.269	n	-
193	MethAmphetamine	Positive test for MethAmphetamine	Substance Use	Breathalyzer and Drug Test Results	0.127	0.239	0.224	n	-
194	Oxycontin	Positive test for Oxycontin	Substance Use	Breathalyzer and Drug Test Results	0.153	0.155	0.183	n	-
195	Endurance_Unadj	NIH Toolbox 2-minute Walk Endurance Test : Unadjusted Scale Score	Motor	Endurance (2 minute walk test)	-0.147	0.172	0.188	y	165
196	Endurance_AgeAdj	NIH Toolbox 2-minute Walk Endurance Test : Age-Adjusted Scale Score	Motor	Endurance (2 minute walk test)	-0.163	0.13	0.169	y	166
197	GaitSpeed_Comp	NIH Toolbox 4-Meter Walk Gait Speed Test: Computed Score	Motor	Locomotion (4-meter walk test)	-0.161	0.134	0.169	y	167
198	Strength_Unadj	NIH Toolbox Grip Strength Test: Unadjusted Scale Score	Motor	Strength (Grip Strength Dynamometry)	0.107	0.323	0.252	y	168
199	Strength_AgeAdj	NIH Toolbox Grip Strength Test: Age-Adjusted-Adjusted Scale Score	Motor	Strength (Grip Strength Dynamometry)	0.107	0.32	0.255	y	169
200	Social_Task_Perc_Random	Social Task Overall Percentage 'Random'	In-Scanner Task Performance	Social	0.053	0.626	0.32	y	170
201	Social_Task_Perc_TOM	Social Task Overall Percentage 'TOM'	In-Scanner Task Performance	Social	-0.096	0.375	0.151	y	171
202	Social_Task_Perc_Unsure	Social Task Overall Percentage 'Unsure'	In-Scanner Task Performance	Social	0.018	0.869	0.194	y	172
203	Social_Task_Perc_NLR	Social Task Overall Percentage No Logged Response	In-Scanner Task Performance	Social	NaN	NaN	NaN	n	-
204	Social_Task_Median_RT_Random	Social Task Overall Reaction Time 'Random'	In-Scanner Task Performance	Social	0.119	0.276	0.244	y	173
205	Social_Task_Median_RT_TOM	Social Task Overall Reaction Time 'TOM'	In-Scanner Task Performance	Social	0.211	0.051	0.119	y	174
206	Social_Task_Median_RT_Unsure	Social Task Overall Reaction Time 'Unsure'	In-Scanner Task Performance	Social	0.316	0.057	0.12	n	-
207	Gambling_Task_Perc_Larger	Gambling Task Overall Percentage 'Larger'	In-Scanner Task Performance	Gambling	0.037	0.734	0.342	y	175
208	Gambling_Task_Perc_Smaller	Gambling Task Overall Percentage 'Smaller'	In-Scanner Task Performance	Gambling	-0.037	0.734	0.34	y	176
209	Gambling_Task_Perc_NLR	Gambling Task Overall Percentage No Logged Response	In-Scanner Task Performance	Gambling	NaN	NaN	NaN	n	-

210	Gambling_Task_Median_RT_Larger	Gambling Task Overall Reaction Time 'Larger'	In-Scanner Task Performance	Gambling	-0.094	0.385	0.269	y	177
211	Gambling_Task_Median_RT_Smaller	Gambling Task Overall Reaction Time 'Smaller'	In-Scanner Task Performance	Gambling	0.044	0.686	0.337	y	178